# Automorphism Groups of the Derivative Relaxations of Rank-One Generated Hyperbolicity Cones

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Symmetric Cones (self-dual and homogeneous)

i \cap

Homogeneous Cones (Automorphism group acts transitively on interior of cone)

i \cap

Spectrahedral Cones \{x \in \mathbb{R}^n : x_1A_1 + \dots + x_nA_n \succeq O\}

\cap
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Hyperbolicity Cones  $\Lambda_+(p, e)$ 

# Hyperbolicity cones

## Hyperbolic polynomial

A homogeneous polynomial  $p \in \mathbb{R}[x_1, \dots, x_n]$  is said to be <u>hyperbolic along</u> direction  $e \in \mathbb{R}^n$  if

- p(e) > 0, and
- for all  $x \in \mathbb{R}^n$ , the univariate polynomial  $t \mapsto p(te x)$  has all real roots.

These roots are called eigenvalues of x and denoted by

$$\lambda_1(x) \ge \lambda_2(x) \ge \cdots \ge \lambda_d(x)$$
, where  $d = \deg p$ .

#### Hyperbolicity cone

For p hyperbolic polynomial along e, define the hyperbolicity cone  $\Lambda_{++}(p, e)$  by

$$\Lambda_{++} := \Lambda_{++}(p,e) := \{x \in \mathbb{R}^n \mid \lambda_1(x) > 0, \ldots, \lambda_d(x) > 0\}$$

We also write the closure of  $\Lambda_{++}$  by

$$\Lambda_+ := \Lambda_+(p, e) := \{ x \in \mathbb{R}^n \mid \lambda_1(x) \ge 0, \dots, \lambda_d(x) \ge 0 \}.$$

(1) The nonnegative orthant  $\mathbb{R}^n_+$  is the hyperbolicity cone  $\Lambda_+(p,e)$  with

$$p(x) = x_1 \cdots x_n, \quad e = (1, \ldots, 1)^T$$

• 
$$p(te-x) = (t-x_1)\cdots(t-x_n)$$
 has roots  $\lambda_i(x) = x_i$ .

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(2) The positive semidefinite cone  $S_{+}^{n}$  is the hyperbolicity cone  $\Lambda_{+}(p, e)$  with

$$p(x) = det(x), e = the identity matrix I_n$$

• The roots of  $P(te - x) = det(tI_n - x)$  are the eigenvalues of symmetric x.

 $\Lambda_+(p, e) = \{x : \text{roots of } t \mapsto p(te - x) \text{ are nonnegative}\}$ 

- $\Lambda_+(p, e)$  is a closed convex cone.
- Generalized Lax Conjecture: Every hyperbolicity cone is a spectrahedral cone.
- Hyperbolic Programming [Güler 1997]:

minimize  $\langle c, x \rangle$  subject to Ax = b,  $x \in \Lambda_+(p, e)$ 

## Derivative relaxation of hyperbolicity cones

For  $k = 1, 2, \ldots, d = \deg p$ , denote

$$D_e^k p(x) := \nabla^k p(x)[e,\ldots,e] \in \mathbb{R}[x_1,\ldots,x_n].$$

Note that  $D_e^k p(x)$  is a homogeneous polynomial of degree d - k (if k < d).

#### Lemma (Gårding 1959)

p is hyperbolic along  $e \Longrightarrow D_e^k p(x)$  is hyperbolic along e, and

 $\Lambda_+(p,e)\subset \Lambda_+(D_e^kp,e).$ 

## Definition: Derivative relaxation (Renegar derivative [Renegar 2006])

The hyperbolicity cone

$$\Lambda^{(k)}_+ := \Lambda^{(k)}_+(p,e) := \Lambda_+(D^k_e p,e)$$

is called the k-th derivative relaxation of  $\Lambda_+(p, e)$ .

$$\Lambda_+ \subset \Lambda^{(1)}_+ \subset \cdots \subset \Lambda^{(d-1)}_+.$$

## Examples

$$\mathbb{R}^{n}_{+} = \Lambda_{+}(p, e)$$
 with  $p(x) = x_{1} \cdots x_{n}, \ e = (1, \dots, 1)^{T}$ .

• The derivative relaxation  $\mathbb{R}^{n,(k)}_+ := \Lambda_+(D^k_e p, e)$  is a hyperbolicity cone.

•  $D_e^k p(x) = k! E_{d-k}(x)$  where  $E_{d-k}(x)$  is the elementary symmetric polynomial

$$E_{d-k}(x) = \sum_{i_1 < \ldots < i_{d-k}} x_{i_1} \cdots x_{i_{d-k}}$$

of degree d - k.

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$$S^n_+ = \Lambda_+(p, e)$$
 with  $P(x) = \det(x), e = I_n$ .

The derivative relaxation S<sup>n,(k)</sup><sub>+</sub> := Λ<sub>+</sub>(D<sup>k</sup><sub>e</sub>p, e) is a hyperbolicity cone.
D<sup>k</sup><sub>e</sub>p(x) = k! E<sub>d-k</sub>(λ(x)).

## Known facts on derivative relaxations

- [Renegar 2006]: investigation of derivative relaxations.
- $\mathbb{R}^{n,(k)}_+$  are spectrahedral cones [Sanyal 2011, Brändén 2014].
- $S^{n,(k)}_+$  are spectrahedral shadows [Saunderson and Parrilo 2015]
- $S^{n,(1)}_+$  is a spectrahedral cone [Saunderson 2018]

Spectrahedral Cones  $\{x \in \mathbb{R}^n : x_1A_1 + \dots + x_nA_n \succeq O\}$   $\cap$ Hyperbolicity Cones  $\Lambda_+(p, e)$ 

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**Our focus**: Geometry of derivative relaxations  $\Lambda_{+}^{(k)}$ , in particular, the structure of their automorphisms.

The automorphism group of a convex cone  $K \subset \mathbb{R}^n$  is the set

 $\operatorname{Aut}(K) := \{A \in \operatorname{GL}_n(\mathbb{R}) : AK = K\}.$ 

Aut(K) provides geometric information on K. We can examine:

- Homogeneity of K: Every  $x, y \in int(K)$  admits Ax = y for some  $A \in Aut(K)$ .
- Lyapunov rank of K [Gowda & Tao 2014]: β(K) := the dimension of the Lie algebra of Aut(K).
- Perfectness of  $K: \beta(K) \ge \dim K$  [Orlitzky & Gowda 2016]

Determination of Aut(K) is difficult for general hyperbolicity cones.  $\rightarrow$  We focus on rank-one generated hyperbolicity cones. The rank of  $x \in \mathbb{R}^n$  is defined by

rank(x) = "the number of nonzero eigenvalues of x"  $\in \{0, 1, \dots, \deg p\}$ 

- $x \in \Lambda_+(p, e)$  has full-rank (i.e., rank $(x) = \deg p$ ) iff  $x \in \operatorname{int} \Lambda_+(p, e)$ .
- If x is an extreme direction of  $\Lambda_+(p, e)$ , i.e.,  $\operatorname{cone}\{x\} = \mathbb{R}_+ x$  is a face of  $\Lambda_+(p, e)$ , then  $1 \leq \operatorname{rank}(x) < \deg p$ .

#### Definition: Rank-one generated hyperbolicity cone

Hyperbolicity cone  $\Lambda_+(p, e)$  is rank-one generated (ROG) if every extreme direction x of  $\Lambda_+(p, e)$  has rank one.

 Symmetric cones (including ℝ<sup>n</sup><sub>+</sub> and S<sup>n</sup><sub>+</sub>) are ROG hyperbolicity cones under an appropriate choice of p.

### Proposition

Let  $\Lambda_+(p, e)$  be a pointed ROG hyperbolicity cone.

- p is the minimal degree polynomial defining  $\Lambda_+$ .
- $D_e^k p$  is the minimal degree polynomial defining  $\Lambda_+^{(k)}$ .

Minimal degree polynomial is unique up to a positive constant factor. Minimalility is important to analyze the automorphisms:

#### Lemma

If p is a minimal degree polynomial defining  $\Lambda_+$ , then  $A \in GL_n(\mathbb{R})$  belongs to  $Aut(\Lambda_+)$  if and only if  $Ae \in int \Lambda_+$  and  $p(x) = \kappa p(Ax)$  for some  $\kappa > 0$ .

#### Theorem [I. & Lourenço, 2022]

Suppose that  $\Lambda_+ = \Lambda_+(p, e)$  is pointed and ROG. Then,

$$\operatorname{Aut}(\Lambda_{+}^{(k)}) = \operatorname{Aut}(\Lambda_{+}) \cap \{A \in \operatorname{GL}_{n}(\mathbb{R}) : Ae = \lambda e, \exists \lambda > 0\}$$

holds for all  $k = 1, 2, \ldots, d - 3$  where  $d := \deg p$ .

Some consequences: Under the assumption of the theorem,

# Example: Description of $Aut(\mathbb{R}^{n,(k)}_+)$ for $n \ge 4$

$$\mathbb{R}^{n}_{+} = \Lambda_{+}(p, e) \text{ with } p(x) = x_{1} \cdots x_{n}, \ e = (1, \dots, 1)^{T}.$$

The derivative  $\mathbb{R}^{n,(k)}_+ = \Lambda_+(D^k_e \rho, e)$  is the hyperbolicity cone associated with the elementary symmetric polynomial  $\sum_{i_1 < \ldots < i_{d-k}} x_{i_1} \cdots x_{i_{d-k}}$  of degree d - k.

$$\mathbb{R}^n_+ \subset \mathbb{R}^{n,(1)}_+ \subset \cdots \subset \mathbb{R}^{n,(n-3)}_+ \subset \mathbb{R}^{n,(n-2)}_+ \subset \mathbb{R}^{n,(n-1)}_+$$

• 
$$\operatorname{Aut}(\mathbb{R}^n_+) = \{\operatorname{Diag}(d)P : d \in \mathbb{R}^n_{++}, P \text{ permutation matrix}\}$$
  
•  $A \in \operatorname{Aut}(\mathbb{R}^{n,(k)}_+) \iff A \in \operatorname{Aut}(\mathbb{R}^n_+) \text{ and } Ae = \lambda e \ (\lambda > 0) \\ \iff A = \operatorname{Diag}(d)P \text{ and } d_1 = d_2 = \cdots = d_n.$ 

#### Corollary

For k = 1, ..., n-3,  $Aut(\mathbb{R}^{n,(k)}_+) = \{\alpha P : \alpha > 0, P \text{ permutation matrix}\}$ 

- The Lyapunov rank of  $\mathbb{R}^{n,(k)}_+$  is 1.
- $\mathbb{R}^{n,(k)}_+$  is not homogeneous, not perfect.

# Example: Description of $Aut(S^{n,(k)}_+)$ for $n \ge 4$

$$S^n_+ = \Lambda_+(p, e)$$
 with  $p(x) = \det(x), e = I_n$ 

We have the derivative relaxations

$$S^n_+ \subset S^{n,(1)}_+ \subset \cdots \subset S^{n,(n-3)}_+ \subset S^{n,(n-2)}_+ \subset S^{n,(n-1)}_+$$

• Aut
$$(S_+^n) = \{ \alpha L_M : \alpha > 0, M \in GL_n(\mathbb{R}) \}$$
, where  $L_M(x) = M x M^T$   
•  $A \in Aut(S_+^{n,(k)}) \iff A \in Aut(S_+^n)$  and  $A(I_n) = \lambda I_n \ (\lambda > 0)$   
 $\iff A = \alpha L_M$  and  $\alpha M M^T = \lambda I_n \ (\alpha, \lambda > 0)$ .

#### Corollary

For 
$$k = 1, \ldots, n-3$$
,  $Aut(S^{n,(k)}_+) = \{\alpha L_M : \alpha > 0, M \text{ orthogonal matrix}\}$ 

• The Lyapunov rank of  $S^{n,(k)}_+$  is  $\frac{n^2-n+2}{2}$  ( $< \dim S^n_+ = \frac{n^2+n}{2}$ ).

• 
$$S^{n,(k)}_+$$
 is not homogeneous, not perfect.

Main result: If  $\Lambda_+(p, e)$  is a pointed and rank-one-generated hyperbolicity cone, then

$$\operatorname{\mathsf{Aut}}(\Lambda^{(k)}_+) = \operatorname{\mathsf{Aut}}(\Lambda_+) \cap \{A \in \operatorname{\mathsf{GL}}_n(\mathbb{R}) : Ae = \lambda e \; (\lambda > 0)\}$$

for  $k = 1, 2, \ldots, d - 3$ .

- $\Lambda_{+}^{(k)}$  are not homogeneous.
- Aut $(\mathbb{R}^{n,(k)}_+)$  and Aut $(S^{n,(k)}_+)$  can be determined  $\rightarrow$  non-homogeneity, imperfectness

#### Further questions:

- Are homogeneous cones ROG?
- Results for more general hyperbolicity cones.

# Thank you for your attention!

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## Key Lemma: Gårding's inequality [Gårding 1959]

For any  $x_1, \ldots, x_d \in \Lambda_{++}(p, e)$ , we have

$$p(x_1)^{1/d} \cdots p(x_d)^{1/d} \leq \frac{\nabla^d p(0)[x_1, \dots, x_d]}{d!}$$

Equality holds iff  $x_1, \ldots, x_d$  are proportional modulo  $\Lambda_+ \cap (-\Lambda_+)$ .